INCREMEMENTAL ALGORITHMS FOR OPTIMIZING MODEL COMPUTATION BASED ON PARTIAL INSTANTIATION*

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It has been shown that mixed integer programming methods can effectively support minimal model, stable model and well-founded model semantics for ground deductive databases. Recently, a novel approach called partial instantiation has been developed which, when integrated with mixed integer programming methods, can handle non-ground logic programs. The goal of this paper is to explore how this integrated framework based on partial instantiation can be optimized. In particular, we develop an incremental algorithm that minimizes repetitive computations. We also develop several optimization techniques to further enhance the efficiency of our incremental algorithm. Experimental results indicate that our algorithm and optimization techniques can bring about very significant improvement in run-time performance. © Elsevier Science Inc., 1997

1. INTRODUCTION

Very active research in the past decade has led to the development of numerous methods for evaluating deductive databases and logic programs. Algorithms, such as magic sets and counting methods, have proven to be very successful for definite and stratified deductive databases [1, 2]. During the past few years, however, several new semantics for disjunctive programs and programs with negations, such as minimal models, stable models, and well-founded models [18, 12, 22], have been

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proposed and widely studied. Recently, it has been shown that mixed integer programming methods can be used to provide a general and rather effective computational paradigm for these semantics [3, 4, 20].

However, like other methods that use linear or integer programming methods for logic deduction [10, 15], the paradigm proposed in [3, 4, 20] is in effect propositional and can only deal with the ground versions of deductive databases, which are normally much larger in sizes than their nonground versions. To solve this problem, Kagan et al. [16, 17] very recently proposed a novel approach, called partial instantiation, which combines unification with mixed integer programming (or with any other propositional deduction techniques), and which can directly solve a nonground version of a program. Equally importantly, the approach can handle function symbols, thus making it a true logic programming computational paradigm. While we will discuss partial instantiation in greater detail in Section 2, the general strategy is to alternate iteratively between two phases:

evaluation (as propositional program) → partial instantiation → evaluation ...

More specifically, the initial step begins with evaluating a given nonground logic program $P$ that may contain disjunctive heads and negations in the bodies as a propositional program using mixed integer programming. This generates a set of true propositional atoms and a set of false propositional atoms. The partial instantiation phase then begins by checking whether unification or "conflict resolution" is possible between atoms in the two sets. If $A$ is an atom in the true set and $B$ is an atom in the false set, the most general unifier for $A$ and $B$ is called a conflict-set unifier. Then for each conflict-set unifier $\theta$ (there can be multiple), clauses in $P$ are instantiated with $\theta$ and added to $P$ for further evaluation. In other words, in the next iteration, the (propositional) program to be evaluated is $P \cup P\theta$. This process continues, until either no more conflict-set unifier is found or the time taken has gone beyond a certain time limit. 1

The main focus of this paper is on how to optimize the run-time performance of the evaluation phase. In particular, as described in [3, 4, 20], the evaluation of program $P$ comprises two steps: a step to reduce the size of $P$, followed by the mixed integer programming step to find the models. Let us represent the operations symbolically as $\text{model}(\text{sizeopt}(P))$. As shown in [3, 4, 20], the operation sizeopt to reduce the size of programs is highly beneficial to the subsequent operation of finding the models. Thus, as far as the partial instantiation paradigm is concerned, if $\theta_1, \ldots, \theta_n$ are all the conflict-set unifiers, an obvious strategy will be to compute $\text{model}(\text{sizeopt}(P \cup P\theta_1)), \ldots, \text{model}(\text{sizeopt}(P \cup P\theta_n))$ one by one. The major problem tackled in this paper is how to compute $\text{sizeopt}(P \cup P\theta_i)$ incrementally. That is, we try to optimize the evaluation phase by reusing $\text{sizeopt}(P)$ to compute $\text{sizeopt}(P \cup P\theta_i), \ldots, \text{sizeopt}(P \cup P\theta_n)$. As will be shown in Example 2.2, our task is complicated by the fact that $\text{sizeopt}$ is not a monotonic operation. The principal contributions of this paper are:

- the development of an algorithm, called Incr, which will be formally proved to be incremental;
- the development of several optimizations which may further reduce the size of a program, save time in computing least models, and avoid processing conflict-set unifiers that are redundant;

1 Partial instantiation may be infinite in the presence of function symbols.
• the implementation and experimental evidence showing that these algorithms and optimizations can lead to significant improvement in run-time efficiency; and

• the implementation of the entire framework that includes both the evaluation and partial instantiation phases.

Excellent work has been done on incremental view maintenance for relational, active and deductive databases [5, 6, 9, 11, 13, 14, 21, 23]. Most relevant to our work here are the proposals for deductive databases. [14] deals with recursive views; [11] is concerned with right-linear chains, [23] focuses on rules with negations, and, last but not least, [13] handles rules with aggregations, recursions, and negations. However, all these proposals are concerned with changes—insertions, deletions, and/or updates—to the external database predicates or the base relations. As such, there are two main differences between the work presented here and the existing ones mentioned above. First, the algorithms we developed focus on handling rules inserted or deleted. Second, the operation under consideration here is not logic deduction, i.e., deducing heads from the bodies of rules. Rather, as will be discussed in greater detail in Section 2, the operation \textit{sizeopt} takes a set $P$ of rules as input and returns a subset $P' \subseteq P$ by deleting rules that will not be useful in subsequent model computations.

The outline of the paper is as follows. Section 2 reviews partial instantiation and the operation \textit{sizeopt}. Section 3 presents an incremental algorithm Incr and proves that it is indeed incremental with respect to \textit{sizeopt}. Section 4 develops several optimizations to further improve the performance of Incr and minimal model computation based on partial instantiation. Section 5 gives implementation details and presents experimental results showing the effectiveness of the algorithms and optimizations.

2. PRELIMINARIES

2.1. Review: Partial Instantiation

As described in [16, 17], computing minimal models of logic programs by partial instantiation can be viewed as expanding and processing nodes of partial instantiation trees. Given a nonground logic program $P$ with disjunctive heads and negations in the bodies, the root node of the partial instantiation tree corresponding to $P$ solves $P$ directly as a propositional program. Consider an example presented in [16] where $P$ is the program consisting of the following clauses:

\[ p(X_1, Y_1) \leftarrow q(X_1, Y_1) \]
\[ q(a, Y_2) \leftarrow \]
\[ q(X_2, b) \leftarrow \]

In the root node, $P$ is solved as the program \{\( A \leftarrow B, C \leftarrow, D \leftarrow \), where $A$, $B$, $C$, and $D$ denote $p(X_1, Y_1)$, $q(X_1, Y_1)$, $q(a, Y_2)$, and $q(X_2, b)$, respectively. For this propositional program, the set of true atoms is $T = \{C, D\}$ and the set of false atoms is $F = \{A, B\}$. “Conflict resolution” then looks for unification between an atom in $T$ with an atom in $F$. For our example, there are two conflict-set unifiers: (a) $\theta_1 = \{X_1 = a, Y_1 = Y_2\}$ and (b) $\theta_2 = \{X_1 = X_2, Y_1 = b\}$. Now for each conflict-set
unifier $\theta_i$, a child node is created which is responsible for the processing of the instantiated program $P \cup P_{\theta_i}$. As shown in Figure 1, the root node of the tree for our example has two child nodes: one corresponds to the program $P_1 = P \cup \{p(a, Y_2) \leftarrow q(a, Y_2)\}$; the other child node corresponds to $P_2 = P \cup \{p(X_2, b) \leftarrow q(X, b)\}$. In the evaluation phase of $P_2$, $P_2$ again is treated as a propositional program whose true and false sets are $T_2 = \{q(a, Y_2), q(X_2, b), p(X_2, b)\}$ and $F_2 = F$. For $T_2$ and $F_2$, there are two conflict-set unifiers which are identical to $\theta_1$ and $\theta_2$. Thus, the node for $P_2$ has two child nodes. Similarly, it is not difficult to verify that the node for $P_1$ also has two child nodes. This process of expanding child nodes and alternating between evaluation and partial instantiation continues. A node is a leaf node if its true and false set of atoms cannot be unified. For our example, the partial instantiation tree is finite and has 11 nodes in total.

2.2. Review: Algorithm SizeOpt

In Figure 1, each node is represented as a rectangular box which computes the true set $T_i$ and false set $F_i$ for a given (nonground) program $P_i$. Not captured in Figure 1, the following shows how this computation can be done (for each node).
Nonoptimized:  \( P_i \Rightarrow \text{models}(P_i) \Rightarrow T_i, F_i \);
Optimized:  \( P_i \Rightarrow \text{Sizeopt}(P_i) \Rightarrow \text{models}(\text{sizeopt}(P_i)) \Rightarrow T_i, F_i \).

- There are two approaches to compute the true and false sets. One obvious way is to solve for the models of \( P_i \) directly. However, as shown in \([3, 4, 20]\), it is typically much more efficient to first reduce the size of \( P_i \) via a procedure called \( \text{sizeopt} \), the details of which will be given below.

- Given what partial instantiation can do and given that the operations \( \text{sizeopt} \) and \( \text{models} \) are used in conjunction with partial instantiation, it is sufficient for \( \text{sizeopt} \) and \( \text{models} \) to treat \( P_i \) as propositional, even though \( P_i \) itself may be nonground. In other words, there is a clear “division of labor”: for a given program that may contain variables, partial instantiation takes care of the variables, whereas \( \text{sizeopt} \) and \( \text{models} \) can stay purely propositional. As shown in the example given in Section 2.1, treating a program as propositional simply entails replacing each predicate with a propositional symbol. This is different from and obviously better than “grounding out” a program by substituting a variable with all possible elements in the Herbrand base of the program. Thus, throughout this paper, it should be kept in mind that even though \( \text{sizeopt} \) and our algorithms are presented as purely propositional, they are indeed immediately applicable to programs that may contain variables (and for that matter, function symbols as well). Furthermore, \( \text{sizeopt} \) and our algorithms are not restricted to model solving techniques that are based on mixed integer programming. Since \( \text{sizeopt} \) and \( \text{models} \) are two independent operations, \( \text{sizeopt} \) and our algorithms work equally well with any propositional model solving algorithms.

We are now in a position to present the details of \( \text{sizeopt} \). Since as far as minimal model computation is concerned, a negative literal in the body of a clause can be moved to become a positive literal in the head, thereafter without loss of generality, we only consider clauses possibly with disjunctive heads, but no negation in the bodies.

**Algorithm SizeOpt** [4]. Input \( P \) and \( S_0 \), the set of atoms that do not appear in the head of any clause in \( P \).

1. Initialize \( Q \) to \( P \), \( Q_d \) to \( \emptyset \), and \( i \) to 0.
2. Set \( R \) to \( \emptyset \).
3. For each clause \( C_i \equiv A_1 \lor \cdots \lor A_m \leftarrow B_1 \land \cdots \land B_n \) in \( Q \) and for some \( B_j \) such that \( B_j \in S_i \):
   (a) delete \( C_i \) from \( Q \);
   (b) add \( C_i \) to \( Q_d \); and
   (c) add \( A_1, \ldots, A_m \) to \( R \).
4. Increment \( i \) by 1 and set \( S_i \) to \( R \).
5. For all \( A \) in \( S_i \) if \( A \) occurs in the head of some clause in \( Q \), delete \( A \) from \( S_i \).
6. If \( S_i \) is empty, then return \( Q \) and \( Q_d \), and halt. Otherwise, go back to Step 2.

Hereafter, we use the notation \( \text{sizeopt}(P) = \langle Q, Q_d \rangle \) to denote the application of the above algorithm on \( P \), where \( Q \) is the set of retained clauses and \( Q_d \) is the set of deleted clauses.
Example 2.1. Let \( P \) be the following program:

\[
\begin{align*}
A &\leftarrow B \land C \\
B \lor D &\leftarrow A \land E \\
B &\leftarrow E \land F \\
D &\leftarrow A
\end{align*}
\] (2.1) (2.2) (2.3) (2.4)

Initially, \( S_0 \) is the set \{C, E, F\}. Thus, after Step 3 in the first iteration of Algorithm SizeOpt, \( Q_d \) consists of clauses 1, 2, and 3, and the only clause remaining in \( Q \) is clause 4. After Step 5, \( S_1 \) is \{A, B\}. In the second iteration of Algorithm SizeOpt, the clause \( D \leftarrow A \) is deleted from \( Q \) and added to \( Q_d \) in Step 3. \( S_2 \) is the set \{D\}. In the third iteration of Algorithm SizeOpt, execution halts as \( Q \) becomes empty.

Example 2.2. Let \( P' \) be the program obtained by adding the following two clauses to \( P \) introduced in the previous example:

\[
\begin{align*}
C \lor G &\leftarrow \\
E &\leftarrow C.
\end{align*}
\] (2.5) (2.6)

When Algorithm SizeOpt is applied to \( P' \), the situation changes drastically. \( S_0 \) is now \{F\}. In the first iteration, clause 3 is the only clause added to \( Q_d \), and \( S_1 \) is empty after Step 5. Thus, the algorithm halts in Step 6 without another iteration.

The above example demonstrates that Algorithm SizeOpt is not monotonic, i.e., \( P_1 \subseteq P_2 \Rightarrow Q_{d,1} \subseteq Q_{d,2} \) where \( \text{sizeopt}(P_1) = \langle \neg, Q_{d,1} \rangle \) and \( \text{sizeopt}(P_2) = \langle \neg, Q_{d,2} \rangle \). It is also easy to see that Algorithm SizeOpt is not antimonotonic either (i.e., \( P_1 \subseteq P_2 \Rightarrow Q_{d,2} \subseteq Q_{d,1} \)). The following lemma, proved in [4], shows that Algorithm SizeOpt preserves minimal models.

Lemma 2.1 [4]. Let \( P \) be a disjunctive deductive database such that \( \text{sizeopt}(P) = \langle Q, Q_d \rangle \). \( M \) is a minimal model of \( P \) iff \( M \) is a minimal model of \( Q \).

3. INCREMENTAL ALGORITHM

Suppose \( P \) is the program considered in a node \( N \) of a partial instantiation tree and \( \theta_1, \ldots, \theta_m \) are all the conflict-set unifiers. As discussed in Section 2.1, node \( N \) has \( m \) children, the \( j \)th of which processes the instantiated program \( P \cup P\theta_j \) (where \( 1 \leq j \leq m \)). As described above, Algorithm SizeOpt can be applied to \( P \cup P\theta_j \) to reduce the number of clauses that need to be processed. However, this approach of applying Algorithm SizeOpt directly may lead to a lot of repeated computations, as Algorithms SizeOpt has already been applied to \( P \) in node \( N \) (and similarly, the programs in the ancestors of \( N \)). To avoid repetitive computations as much as possible, we develop Algorithm Incr that reuses \( \text{sizeopt}(P) \) to produce \( \text{sizeopt}(P \cup P\theta_j) \), as shown in Figure 2.
3.1. Graphs for Maintaining Deleted Clauses

Recall from Section 2 that \textit{sizeopt}(P) produces the pair \((Q, Q_d)\), where \(Q_d\) consists of clauses deleted from \(P\). To facilitate incremental processing, Algorithm \texttt{Incr} uses a directed graph \(G\), called a DC-graph, to organize the deleted clauses. The intended properties of a DC-graph are as follows.

- Nodes represent atoms that do not appear in the head of any clause in \(Q\).
- If there is an arc from node \(B_i\) to \(A\), then the arc is labeled by a clause \(C_1 \in Q_d\) such that \(A\) appears in the head of \(C_1\) and \(B_i\) occurs in the body of \(C_1\).

The only exceptions to the above properties are the special root node and the arcs originating from this root node. As will be shown later, the root node is the place where a graph traversal begins. Arcs that originate from the root node are not labeled, as those arcs do not correspond to any clause in \(Q_d\).

\textit{Example 3.1.} Consider the program \(P\) discussed in Example 2.1. \(Q_d\) consists of all four clauses in \(P\). Figure 3 shows the DC-graph \(G_1\) corresponding to \(Q_d\). For convenience, arcs are labeled by the clause numbers used in Example 2.1. Furthermore, the label 2,3 of the arc from \(E\) to \(B\) is a shorthand notation that represents two arcs from \(E\) to \(B\) with labels 2 and 3, respectively. Notice that \(G_1\) contains a cycle between \(A\) and \(B\).

This example only illustrates how DC-graph \(G_1\) looks. We will show in Example 3.2 how \(G_1\) can be constructed, after Algorithm \texttt{Incr} has been presented. However, before we can present the algorithm, we need the following concept.
3.2. Self-Sustaining Cycles

Definition 1. Let \( A_1 \rightarrow_{c_1} A_2 \rightarrow_{c_2} \cdots \rightarrow_{c_{i-1}} A_i \rightarrow_{c_i} A_1 \) be a cycle in DC-graph \( G \), where \( A \rightarrow_{c_i} B \) denotes an arc from \( A \) to \( B \) with label \( c_i \). If there does not exist any arc from outside the cycle to some \( A_j \) with label \( c_{i-1} \) (i.e., \( \not\exists B \rightarrow_{c_{i-1}} A_i \) for some \( B \notin \{A_1, \ldots, A_n\} \)), then the cycle is called self-sustaining.

As shown in the above example, \( G_1 \) contains the cycle \( A \rightarrow_{c_1} B \rightarrow_{c_1} A \). This cycle is not self-sustaining because of the arc \( C \rightarrow_{c_1} A \) (or the arc \( E \rightarrow_{c_1} B \)). The existence of this arc justifies why clause 1 should be deleted and why \( A \) should remain a node in the graph. On the other hand, if the arcs \( C \rightarrow_{c_1} A \) and \( E \rightarrow_{c_1} B \) were removed, the cycle \( A \rightarrow_{c_1} B \rightarrow_{c_1} A \) became self-sustaining. Then for the sake of achieving the kind of incrementality depicted in Figure 2, clause 2 should be restored (i.e., no longer be kept in \( Q_d \)). This would cause node \( B \) to disappear from the graph, which in turn leads to the restoration of clause 1 and the disappearance of node \( A \). Example 3.3 below will give further details as to why all these actions are necessary. In general, if there exists a self-sustaining cycle in a DC-graph, all the clauses involved in the cycle need to be restored and all the nodes of the cycle need to be removed. We are now in a position to present Algorithm Incr.

3.3. Algorithm Incr

Algorithm Incr. Input \( P = (Q, Q_d) \), the DC-graph \( G \) corresponding to \( Q_d \), and a clause \( C_1 = A_1 \lor \cdots \lor A_m \rightarrow B_1 \land \cdots \land B_n \) to be added to \( P \).

1. For each \( B_i \) that does not appear in \( Q \) and \( Q_d \) (i.e., appearing in \( P \) the first time), add to graph \( G \) a node \( B_i \) and an arc from the root to node \( B_i \).
2. For each \( B_i \) that is a node:
   (a) For each \( A_j \), where \( 1 \leq j \leq m \):
      (i) If \( A_j \) does not appear in \( Q, Q_d, \) and \( G \), add node \( A_j \) to \( G \).
      (ii) If there is a node \( A_j \) in \( G \), add an arc from node \( B_i \) to node \( A_j \) labeled \( c_i \). If there is originally an arc from the root to node \( A_j \), remove that arc.
   (b) Add \( C_1 \) to \( Q_d \).
3. If there is no such \( B_i \) in the previous step:
   (a) Add \( C_1 \) to \( Q \).
   (b) For each \( A_j \) that appears as a node in \( G \), where \( 1 \leq j \leq m \), call Subroutine Remove(\( A_j \)).
4. For each self-sustaining cycle in \( G \), call Subroutine Remove(\( D \)), where \( D \) is some atom in the cycle.

Subroutine Remove. Input atom (node) \( A \).

1. Remove from graph \( G \) node \( A \) and all the arcs pointing to \( A \).
2. For each arc initially originating from \( A \) in \( G \) (i.e., \( A \rightarrow_{c_1} B \)):
   (a) Remove the arc from \( G \).
(b) If there does not exist another arc pointing to \( B \) with label \( C_1 \) (i.e., \( \not\exists D \rightarrow C_1 B \) for some \( D \)):

(i) Remove \( C_1 \) from \( Q_d \) and add it to \( Q \).

(ii) Call Subroutine Remove(\( B \)) recursively.

3. For each clause \( C_1 \) in \( Q_d \) such that \( A \) appears in the body of \( C_1 \), if all atoms in the body of \( C_1 \) do not appear as nodes in \( G \), remove \( C_1 \) from \( Q_d \) and add it to \( Q \).

Hereafter, we use the notation \( \text{incr}(\langle Q, Q_d, G \rangle, C_1) = \langle Q_{\text{out}}, Q_d, G_{\text{out}} \rangle \) to denote the fact that when Algorithm Incr is applied to inputs \( Q \) (the original set of retained clauses), \( Q_d \) (the original set of delete clauses), \( G \) (the DC-graph corresponding to \( Q_d \)), and \( C_1 \) (the clause to be inserted), the outputs are \( Q_{\text{out}} \) (new set of retained clauses), \( Q_d \) (new set of delete clauses), and \( G_{\text{out}} \) (new DC-graph). Moreover, we abuse notation by using \( \emptyset \) to denote an empty DC-graph, i.e., the DC-graph with the root node only.

Example 3.2. Apply Algorithm Incr to the four clauses in the program \( P \) discussed in Example 2.1. In Figure 4, the first DC-graph [labeled (i)] is graph \( G_{r_1} \), where \( \text{incr}(\langle \emptyset, \emptyset, \emptyset \rangle, C_1) = \langle \emptyset, \{C_1\}, G_{r_1} \rangle \). This is the case because nodes \( B \) and \( C \) are added in Step 1 of Algorithm Incr; node \( A \) and the two arcs pointing to \( A \) are added in Step 2a. Steps 3 and 4 are not needed in this case.

Similarly, the second graph in Figure 4 is DC-graph \( G_{r_2} \) where

\[
\text{incr}(\langle \emptyset, \{C_1\}, G_{r_1} \rangle, C_1) = \langle \emptyset, \{C_1, C_2\}, G_{r_2} \rangle.
\]

This time, node \( E \) is added in Step 1 of Algorithm Incr and the four arcs pointing from \( A \) and \( E \) to \( B \) and \( D \) are added in Step 2a. Notice that even though there is a cycle in \( G_{r_2} \), the cycle is not self-sustaining. It is also not difficult to verify that \( \text{sizeopt}(\langle C_1, C_2 \rangle) = \langle \emptyset, \{C_1, C_2\} \rangle \).

Similarly, the third graph in Figure 4 is produced by applying Algorithm Incr to add \( C_3 \) to \( G_{r_2} \), and the fourth one (called \( G_{r_1} \) in Example 3.1) is produced by applying Incr to \( C_4 \) and the third graph. Finally, the graphs in Figure 5 show the DC-graphs obtained by applying Algorithm Incr to insert the four clauses in the reverse order. As expected, the fourth DC-graphs in Figures 4 and 5 are the same. Later we will show that inserting the clauses in different orders give identical end result.

![FIGURE 4. Applying Algorithm Incr to add clauses 1, 2, 3, and 4.](image-url)
The above example only demonstrates the situation when an inserted clause ends up being added to the set $Q_d$ (i.e., $Q_d$ keeps growing). Obviously, this is not always the case, as an inserted clause may indeed end up being added to the set $Q$. This addition may trigger a series of node removals and the shrinkage of $Q_d$.

**Example 3.3.** Now consider program $P'$, that is, adding clauses 5 and 6 discussed in Example 2.2. Let us add clause 5 first. Steps 1 and 2 of Algorithm Incr are not invoked, but in Step 3a, the clause is added to $Q$ and Subroutine Remove($C$) is called. In Step 1 of Subroutine Remove, node $C$ and the arc from the root to $C$ are removed. As for the arc from $C$ to $A$ labeled $C_{15}$, this arc is removed, but because of the existence of the arc from $B$ to $A$ labeled $C_{14}$, Subroutine Remove is not called recursively. Furthermore, Step 3 of Remove does not cause any change, and control returns to Algorithm Incr. As for Step 4 of Algorithm Incr, even though there is a cycle from between $A$ and $B$, this cycle is not self-sustaining because of the arc from $E$ to $B$ with label $C_{15}$. Thus, Algorithm Incr halts. In functional terms, we have $\text{incr}(\emptyset, \{C_1, ..., C_{14}\}, G_1, C_{15}) = (\{C_1\}, \{C_1, ..., C_{14}\}, G_{r_5})$, where $G_{r_5}$ is the first DC-graph shown in Figure 6. Before we proceed, note that it is not difficult to verify that $\text{sizeopt}(\{C_1, ..., C_{15}\}) = (\{C_{15}\}, \{C_1, ..., C_{14}\})$.

Now let us add clause 6. Steps 1 and 2 of Algorithm Incr are not invoked, but in Step 3a, the clause is added to $Q$ and Subroutine Remove($E$) is called. In Step 1 of Subroutine Remove, node $E$ and the arc from the root to $E$ are removed. As for the arc from $E$ to $B$ labeled $C_{15}$, this arc is removed, but because of the existence of the arc from $A$ to $B$ labeled $C_{14}$, Subroutine Remove is not called recursively. Similarly, the arc from $E$ to $B$ labeled $C_{15}$ and the arc from $E$ to $D$ labeled $C_{13}$ are deleted without recursively calling Remove. Furthermore, Step 3 of Remove does not cause any change, and control returns to Algorithm Incr. The second DC-graph in Figure 6 shows the situation at this point.

However, unlike the above situation for clause 5, this time the cycle between $A$ and $B$ is self-sustaining. Thus, in Step 4 of Algorithm Incr, Subroutine Remove($B$) is called. Step 1 of Remove($B$) causes node $B$ and the two arcs from $F$ and $A$ to

\[\text{It is not difficult to verify that the result is the same, if Remove($A$) is called first.}\]
$B$ to be deleted. In Step 2, the arc from $B$ to $A$ is also removed; clause 1 is moved from $Q_d$ to $Q$; and this time Subroutine Remove($A$) is invoked recursively. In Step 1 of Remove($A$), node $A$ is erased. In Step 2, the arc from $A$ to $D$ is removed; clauses 2 and 4 are moved from $Q_d$ to $Q$; and Subroutine Remove($D$) is called recursively.

Step 1 of Remove($D$) erases node $D$, and Step 3 causes no change. Control now returns to Step 3 of Remove($A$). As there is no longer any clause in $Q_d$ with $A$ in the body, control returns to Step 3 of Remove($B$). Again as there is no longer any clause in $Q_d$ with $B$ in the body, the executions of Remove($B$) and Algorithm Incr are now completed. In functional terms, we have

$$\text{incr}(\langle \{C_1, \ldots, C_4\}, G_{r_5} \rangle, C_{15}) = \langle \{C_1, C_2, C_4, C_5, C_6\}, \{C_{13}\}, G_{r_6} \rangle,$$

where $G_{r_6}$ is the last DC-graph shown in Figure 6.

As shown in Example 2.2 we have

$$\text{sizeopt}(\{C_1, \ldots, C_6\}) = \langle \{C_1, C_2, C_4, C_5, C_{13}\}, \{C_{13}\} \rangle,$$

verifying once again the incremental nature of Algorithm Incr. As detailed above, this is due largely to Step 4, without which the final situation would be as shown in the second DC-graph of Figure 6, but not as in the third graph.

**Example 3.4.** Thus far, we have not seen a situation in which Step 3 of Subroutine Remove is needed, but given the third graph in Figure 6, let us consider adding the clause $F \leftarrow A$ to the existing program. Since $A$ appears in $Q$, Step 3 of Algorithm Incr adds the clause to $Q$ and calls Remove($F$). Now in Step 3 of Remove($F$), clause 3—which is in $Q_d$, but does not appear as a label in $G$—is correctly inserted into $Q$ from $Q_d$.

**3.4. Correctness Proof: Incrementality of Algorithm Incr**

In the remainder of this section, we present one of the key results of this paper—the theorem proving the incremental property of Algorithm Incr (cf. Theorem 3.1). This property has been verified several times in the previous examples. Before we can prove the theorem, we need the following lemmas.
Lemma 3.1. Let $P$ be the set $\{C_1, \ldots, C_n\}$. Then:

1. Let $\text{sizeopt}(P) = (Q, Q_d)$. This is the case that $Q \cup Q_d = P$ and $Q \cap Q_d = \emptyset$.
2. Let $\text{incr}(\ldots \text{incr}(\emptyset, \emptyset, \emptyset), C_1, \ldots, C_n) = (P_n, P_{n,d}, G_n)$. This is the case that $P_n \cup P_{n,d} = P$ and $P_n \cap P_{n,d} = \emptyset$.

Proof Outline. For part 1, as shown in Algorithm SizeOpt, $Q$ is initialized to $P$ and $Q_d$ to $\emptyset$ in Step 1. Afterward, the only place where a clause is removed is in Step 3. More specifically, as shown in Steps 3a and 3b, whenever a clause is removed from $Q$, that clause is added to $Q_d$. Thus, it is obvious that part 1 of the lemma is true.

For part 2, let us prove by induction on $n$. When $n = 1$, it is obvious that Subroutine Remove is not invoked in Algorithm Incr. If $C_1$ is of the form $A_1 \lor \cdots \lor A_m \leftarrow$, then by Step 3, $P_1 = \{C_1\}$ and $P_{1,d} = \emptyset$. Otherwise, $C_1$ is of the form $A_1 \lor \cdots \lor A_m \leftarrow B_1 \land \cdots \land B_q$. Then by Step 2, $P_1 = \emptyset$ and $P_{1,d} = \{C_1\}$. Hence, in both cases, $P_1 \cup P_{1,d} = \{C_1\}$ and $P_1 \cap P_{1,d} = \emptyset$.

Now assume that part 2 of the lemma is true for $n = k - 1$. There are two cases. First, consider the case when Subroutine Remove is not called. Then Steps 2 and 3 are the only places when a clause is either added to $P_k$ or $P_{k,d}$. Notice that the conditions of Steps 2 and 3 are mutually exclusive to each other. Thus, given the induction assumption that $P_{k-1} \cup P_{k-1,d} = \{C_1, \ldots, C_{k-1}\}$ and $P_{k-1} \cap P_{k-1,d} = \emptyset$, it is the case that $P_k \cup P_{k,d} = \{C_1, \ldots, C_k\}$ and $P_k \cap P_{k,d} = \emptyset$.

Second, consider the case when Subroutine Remove is invoked. The two places in Remove when a clause is moved around are Steps 2a and 3. More specifically, whenever a clause is deleted from $P_{k-1}$, it is immediately added to $P_k$. Thus given the induction assumption, it is necessary that regardless of how many times Remove is invoked, $P_k \cup P_{k,d} = \{C_1, \ldots, C_k\}$ and $P_k \cap P_{k,d} = \emptyset$.

The lemma above shows that for both Algorithm SizeOpt and Algorithm Incr, the set of retained clauses and the set of deleted clauses partition the original program $P$. The lemma below shows that node $A$ appears in a DC-graph if and only if all clauses with $A$ in the heads have already been deleted.

Lemma 3.2. Let $\text{incr}(\ldots \text{incr}(\emptyset, \emptyset, \emptyset), C_1, \ldots, C_n) = (P_n, P_{n,d}, G_n)$. Then for any atom $A$, $A$ appears as a node in $G_n$ iff there does not exist any clause in $P_n$ with $A$ in the head.

Proof Outline. Prove by induction on $n$. When $n = 1$, it is obvious that Subroutine Remove is not invoked in Algorithm Incr. If node $A$ appears in the DC-graph, the node must be added in Step 2a. Then by Step 2c, $C_1$ is added to $P_{1,d}$ and is not in $P_1$. Conversely, if $C_1$ appears in $P_1$, then it must be added to $P_1$ in Step 3a. In that case, Step 2a is not executed and $A$ does not appear in the DC-graph. Now assume that the lemma is true for $n = k - 1$. There are two cases.

Case I. Subroutine Remove is not called. For any atom $A$, there are two subcases.

Case I.1. $A$ does not appear in the head of $C_1$. If $A$ does not appear in the body of $C_1$, then $A$ appears as a node in $G_k$ iff $A$ appears as a node in $G_{k-1}$, as Subroutine Remove is not invoked. By the induction assumption, $A$ appears in $G_k$ iff there does not exist any clause in $P_{k-1}$ with $A$ in the head. Since $A$ is not the
head of Cl_k, it is necessary that there does not exist any clause in P_k with A in the head.

Now consider the case when A appears in the body of Cl_k. If A appears in either P_{k-1} or P_{k-1,d}, then A appears as a node in G_k iff A appears as a node in G_{k-1}. The situation is exactly the same as the one considered in the previous paragraph. Otherwise, if A appears for the first time, then node A is added to G_k in Step 1, but obviously P_k still does not contain any clause with A in the head.

Case 1.2. A appears in the head of Cl_k. There are two subcases, depending on whether Step 2 or 3 is executed. If Step 3 is executed, then Cl_k is in P_k by Step 3a, but then Step 3b guarantees that G_k does not contain node A. On the other hand, if Step 2 is executed instead, there are two more subcases. If A appears in either P_{k-1} or P_{k-1,d}, then A appears as a node in G_k iff A appears as a node in G_{k-1}. The situation is then similar to the one considered in the first paragraph of Case 1.1. Otherwise, if A appears for the first time, then node A is added to G_k in Step 2a, but not added to P_k. By the induction assumption, since node A does not appear in G_{k-1}, there is no clause in P_{k-1} with A in the head. Thus, as Cl_k is added to P_{k,d}, there is no clause in P_k with A in the head. This completes the analysis of Case 1.

Case 2. Subroutine Remove is invoked. For any atom A, there are two subcases.

Case 2.1. Remove(A) is invoked. There are three places where Remove(A) can be invoked. If Remove(A) is called from Step 3b of Incr, then in Step 3a a clause with A in the head is added to P_k. If Remove(A) is called recursively in Step 2b of Remove(B) for some B, B \rightarrow A Cl A is the only arc pointing to A with label Cl for some clause Cl with A in the head. Then in Step 2b of Remove(B), Cl is moved from P_{k-1,d} to P_k. Finally, if Remove(A) is called from Step 4 of algorithm Incr, A is in a self-sustaining cycle. Step 2 of Remove(A) recursively causes all nodes in the self-sustaining cycle be removed. Thus, at least one clause with A in the head is moved from P_{k-1,d} to P_k.

Case 2.2. Remove(A) is not invoked. The analysis for this case is very similar to that for Case 1. This completes the proof of this lemma. □

We need one more lemma before we can prove Theorem 3.1. This lemma requires the following concept.

Definition 2. Let A be a node in a DC-graph G. The rank of A in G, denoted by rank(A), is defined recursively as follows:

1. If there is an arc from the root to A, rank(A) = 0.
2. Let B_{1,1}, \ldots, B_{1,u_1}, \ldots, B_{m,1}, \ldots, B_{m,u_m} be all the nodes that have arcs pointing to A, such that (a) \{Cl_{1,1}, \ldots, Cl_{m,1}\} are all the labels of these arcs and (b) for all 1 \leq j \leq m, B_{j,1}, \ldots, B_{j,u_j} are all the nodes that have arcs pointing to A with label Cl_{j}. Then rank(A) = 1 + \max_{1 \leq j \leq m}(\min_{1 \leq i \leq u_j} \text{rank}(B_{j,i})).
Example 3.5. Consider the DC-graph $G_1$ introduced in Figure 2. The nodes with rank $= 0$ are $C$, $E$, and $F$. Now consider rank($A$). There are the arcs from $C$ and $B$ pointing to $A$, both with label $C_1$. Thus, rank($A$) = $1 + \min\{\text{rank}(C), \text{rank}(B)\}$. Since rank($C$) = 0, it is obvious that rank($A$) = $1 + \text{rank}(C) = 1$. Now consider rank($B$) and all the arcs pointing to $B$. This time there are two different labels: $C_2$ and $C_3$. For $C_2$, there are the arcs from $A$ and $E$ to $B$. Based on an analysis similarly to that for rank($A$), the minimum corresponding to $C_2$ is rank($E$) = 0. For $C_3$, there are the arcs from $E$ and $F$ to $B$. Thus, the minimum based on $C_3$ is $\min\{\text{rank}(E), \text{rank}(F)\} = 0$. Hence, rank($B$) = $1 + \max\{0, 0\} = 1$, where the two zeros correspond to $C_2$ and $C_3$, respectively. Similarly, it is not difficult to verify that rank($D$) = $1 + \text{rank}(A) = 2$. Now compare the ranks with the sets $S_0$, $S_1$, and $S_2$ discussed in Example 2.1. The interesting thing here is that for all atoms $A$, rank($A$) = $k$ iff $A \in S_k$. This property will be proved formally in the lemma below.

Notice that if a DC-graph contains a self-sustaining cycle, rank assignments to atoms in the cycle are not well defined. For example, consider the self-sustaining cycle between $A$ and $B$ in the second DC-graph in Figure 6. Then rank($B$) depends on rank($A$), which in turns depends on rank($B$). Thus, both ranks are not well defined because of the cyclic dependency. Fortunately, since Step 4 of Algorithm Incr removes all self-sustaining cycles, all DC-graphs produced by Incr do not contain any self-sustaining cycle. Then by Definition 1, for the non self-sustaining cycle $A_1 \rightarrow C_1$, $A_2 \rightarrow C_2$, ..., $A_n \rightarrow C_n A_1$, there must exist atom $A_i$ such that there exists arc $B \rightarrow C_{i-1}$, $A_i$ for some atom $B \in \{A_1, \ldots, A_n\}$. Thus, in determining rank($A_i$), for clause $C_{i-1}$, $\min\{\text{rank}(B), \text{rank}(A_{i-1})\}$ is always well defined (cf. the previous example). Thus, there is no cyclic dependency on rank assignments.

Lemma 3.3. Let incr($(Q, Q_d, G), C_1) = (Q_{\text{out}}, Q_{d_{\text{out}}}, G_{\text{out}})$. Then for all nodes $A \in G_{\text{out}}$, rank($A$) = $n$ iff $A \in S_n$, where the sets $S_0, \ldots, S_n$ are the ones produced by applying Algorithm SizeOpt directly on $Q_{\text{out}} \cup Q_{d_{\text{out}}}$.

Proof Outline. Prove by induction on $n$. When $n = 0$, rank($A$) = 0 iff there is an arc from the root to $A$. This arc is created in Step 1 of Algorithm Incr. If this arc is not removed in Step 2b, it must be the case that $A$ does not appear in the head of any clause in $Q_{\text{out}} \cup Q_{d_{\text{out}}}$. Then when applying Algorithm SizeOpt directly on $Q_{\text{out}} \cup Q_{d_{\text{out}}}$, it is necessary that $A \in S_0$. Assume that the lemma is true for $n = k - 1$. We prove the if and only-if parts separately.

Case 1. rank($A$) = $k$. By Definition 2, rank($A$) = $1 + \max_{i \leq m} \left( \min_{i \leq j < m} \text{rank}(B_{i,j}) \right)$. That is, among the clauses $C_1, \ldots, C_m$ that are the labels of all the arcs pointing to $A$, there exists one clause $C_j$ where $1 \leq j \leq m$ such that rank($A$) = $k = 1 + \left( \min_{i \leq j < m} \text{rank}(B_{i,j}) \right)$. More specifically, $C_j$ must be of the form $\ldots A \ldots \leftarrow \ldots \land B_{1,i} \land \ldots \land B_{i-1,i} \land \ldots$. Among these $u_i$ atoms, let $i$ be the one so that rank($B_{i,i}$) = $\min_{i \leq j < m} \text{rank}(B_{i,j})$. In other words, rank($B_{i,i}$) = $k - 1$. By the induction assumption, $B_{i,i} \in S_{k-1}$. Thus, in Step 3 of Algorithm SizeOpt, $C_j$ is removed and $A$ is added to the set $R$. By applying a similar argument, it is obvious that all clauses $C_1, \ldots, C_m$ must be removed at some iteration of Algorithm SizeOpt. More specifically, since $C_j$ corresponds to the maximum "minimum-rank," $C_j$ must be
the last clause deleted with $A$ appearing in the head. Thus, there must not exist any retained clause with head $A$. Hence, in Step 5 of Algorithm SizeOpt, $A$ is kept in the set $S_k$.

**Case 1.** $A \in S_k$. As shown in Algorithm SizeOpt, there must exist clause $C_l$ of the form $\cdots \cdots \cdots B_{j_1} \cdots B_{j_n}$, such that this is (one of) the last clause with $A$ in the head, and $B_{j_i}$ is in $S_{k-1}$. By the induction assumption, $\text{rank}(B_{j_i}) = k - 1$. Now among all $B_{j_1}, \ldots, B_{j_n}$ that appear in the body of $C_l$ and that appear as nodes in the DC-graph, suppose there exists $B_{j_1}$ such that $\text{rank}(B_{j_1}) < k - 1$. By the induction assumption, $B_{j_1} \in S_{w}$, where $w < k - 1$. In that case, by Step 3 of Algorithm SizeOpt, the clause $C_l$ must have been deleted earlier and should not exist for deletion in the current iteration. This is a contradiction. Thus, it is necessary that $\text{rank}(B_{j_1}) = \text{rank}(B_{j_n}) = \text{rank}(B_{j_i}) = \max\{B_{j_1}, \ldots, B_{j_n}\}$. Hence, it is necessary that $\text{rank}(A) = 1 + \text{rank}(B_{j_i}) = k$. \[ \square \]

Now we are in a position to present the theorem that proves the incremental property of Algorithm Incr.

**Theorem 3.1.** Let $P$ be a program consisting of clauses $C_1, \ldots, C_n$. Let $\text{sizeopt}(P) = (Q, Q_d)$ and let $\text{incr}(\cdots \text{incr}(\langle\emptyset, \emptyset, \emptyset\rangle, C_1), \ldots, C_n) = (P_n, P_{n,d}, G_n)$. Then $Q = P_n$ and $Q_d = P_{n,d}$.

**Proof Outline.** Given Lemma 3.1, it suffices to prove $Q_d = P_{n,d}$. Let $C_l \equiv \cdots A \cdots B_i \land \cdots B_m$ be a clause in $Q_d$.

**Case 1.** No clause in $Q$ with $A$ in the head. Then all clauses with $A$ in the head are in $Q_d$ and for some $k$, $A \in S_k$. By Lemma 3.3, this is true iff $\text{rank}(A) = k$. By Lemma 3.2, this is possible iff all clauses with $A$ in the heads have been deleted, i.e., in $P_{n,d}$.

**Case 2.** Some clause exists in $Q$ with $A$ in the head. $C_l$ is in $Q_d$ iff there exists $B_j$, where $1 \leq j \leq m$, such that $B_j \in S_k$ for some $k$. By Lemma 3.3, this is true iff $\text{rank}(B_j) = k$. There are now two subcases depending on whether node $B_j$ appears in the DC-graph when $C_l$ was inserted by Algorithm Incr.

**Case 2.1.** Node $B_j$ already created. Then by Step 2c of Algorithm Incr, $C_l$ is added to the set of deleted clauses.

**Case 2.2.** Otherwise. Suppose $C_l$ does not represent the first time $B_j$ appears. Let $C_l$ be the clause when $B_j$ first appears. Since there does not exist node $B_j$ in the DC-graph, $B_j$ must be in the head of $C_{l_1}$, as ensured by Step 1 of Algorithm Incr. Furthermore, because of Step 2 and because there does not exist mode $B_j$ in the graph, $C_l$ must be added to the set of retained clauses in Step 3. However, notice that in Algorithm Incr and Subroutine Remove, once a clause is put into the set of retained clauses, it will never be removed. In other words, $C_l$ must be in $P_n$. However, by Lemma 3.2, $B_j$ cannot be a node in the graph $G_n$ and $\text{rank}(B_j)$ cannot...
be equal to $k$. This is a contradiction. Hence, it is necessary that $C_l$ represents the first time $B_j$ appears. Thus, in Step 1 of Algorithm Incr, a node for $B_j$ is created and the situation is exactly the same as in Case 2.1.

Combining Cases 2.1 and 2.2, it is necessary that $C_l$ was once added to the set of deleted clauses. Now since $B_j$ is a node in the DC-graph, Step 3 of Subroutine Remove will never remove $C_l$ from the set of deleted clauses. Hence, it is necessary that $C_l$ is in $P_{n,d}$. This completes the proof of the theorem. □

Corollary 3.1. Given clauses $C_{l_1}, \ldots, C_{l_n}$, Algorithm Incr produces the same end result regardless of the order $C_{l_1}, \ldots, C_{l_n}$ are inserted.

4. FURTHER OPTIMIZATIONS

In the previous section, we have presented Algorithm Incr and showed that it achieves the kind of incrementality shown in Figure 2. In this section, we will develop several ways to optimize this algorithm and the expansion and computation of a partial instantiation tree.

4.1. Algorithm IncrOpt

A complexity analysis on Algorithm Incr reveals that Step 4 plays a considerable role in determining the efficiency of Incr. It involves finding each and every self-sustaining cycle that may exist in the DC-graph. As shown in Example 3.3, this is the crucial step that leads to the incremental property of Algorithm Incr. However, the following lemma shows that from the point of view of computing minimal models, self-sustaining cycles need not be detected and can be left in the graph.

Lemma 4.1. Let $Q$ be a set of retained clauses and let $Q_d$ be a set of deleted clauses maintained in the DC-graph $G$. Let $A_1 \rightarrow C_l, A_2 \rightarrow C_l, \ldots \rightarrow C_l, A_{l+1} \ldots A_n \rightarrow C_l, A_1$ be a self-sustaining cycle in $G$. $M$ is a minimal model of $Q \cup \{C_{l_1}, \ldots, C_{l_n}\}$ iff $M$ is a minimal model of $Q$.

Proof Outline. As introduced in Section 3.1, for all $1 < i < n$, $C_l$ is a clause with $A_{i+1}$ in the head and $A_i$ in the body. Since $A_1, \ldots, A_n$ are nodes in DC-graph $G$, none of $A_1, \ldots, A_n$ appears in $Q$. Thus, given any minimal model $M$ of $Q$, none of $A_1, \ldots, A_n$ is contained in $M$. Then it is easy to see that $M$ is a model of $C_{l_1}, \ldots, C_{l_n}$. Hence, $M$ is a minimal model of $Q \cup \{C_{l_1}, \ldots, C_{l_n}\}$ iff $M$ is a minimal model of $Q$. □

The above lemma motivates the following algorithm.

Algorithm IncrOpt. Exactly the same as Algorithm Incr, but without Step 4 of Incr.

Hereafter we use the notation $incropt(Q, Q_d, G, C_l) = (Q_{out}, Q_{d_{out}}, G_{out})$ for Algorithm IncrOpt in exactly the same way as we use $incr(Q, Q_d, G, C_l) = (Q_{out}, Q_{d_{out}}, G_{out})$ for Incr. The corollary below follows directly from Lemma 2.1, Theorem 3.1, and Lemma 4.1.
Corollary 4.1. Let $P$ be a program consisting of clauses $C_1, \ldots, C_n$ and let 
\[
\text{incropt}(\ldots \text{incropt}(\langle \emptyset, \emptyset, \emptyset \rangle, C_1), \ldots, C_n) = \langle P_n, P_{n,d}, G_n \rangle.
\]
$M$ is a minimal model of $P$ iff $M$ is a minimal model of $P_n$.

As far as supporting minimal model computation is concerned, Algorithm IncrOpt is more preferable than Algorithm Incr. The reasons are threefold.

- First, as discussed above, IncrOpt does not check for self-sustaining cycles. While cycle detection takes time linear to the number to edges in the graph, checking all cycles to see whether they are self-sustaining takes considerably more time. Thus, by not checking self-sustaining cycles, IncrOpt is more efficient than Incr.

- Second, it is easy to see if 
\[
\text{incropt}(\langle Q, Q_d, G \rangle, C_1) = \langle \text{out}, \text{out} \rangle
\]
and
\[
\text{incr}(\langle Q, Q_d, G \rangle, C_1) = \langle \text{out}, \text{out} \rangle.
\]
Then it is necessary that $\langle \text{out} \rangle$. More precisely, IncrOpt keeps all clauses in self-sustaining cycles deleted. Thus, the size of the program $Q_{\text{out}}$ may be much smaller than that of $Q_{\text{out}}\text{opt}$. The implication is that finding the minimal models based on $Q_{\text{out}}$ may take considerably less time than finding the minimal models based on $Q_{\text{out}}\text{opt}$.

- The third reason why Algorithm IncrOpt is more preferred applies only to programs $P$ that are definite (i.e., no disjunctive heads). The following lemma shows that for such programs $P$, Algorithm IncrOpt directly finds the least model of $P$.

Lemma 4.2. Let $P$ be a definite program consisting of clauses $C_1, \ldots, C_n$ and let 
\[
\text{incropt}(\ldots \text{incropt}(\langle \emptyset, \emptyset, \emptyset \rangle, C_1), \ldots, C_n) = \langle P_n, P_{n,d}, G_n \rangle.
\]
The least model of $P$ is the set $\{A | A$ is the head of a clause in $P_n\}$.

**Proof Outline.** Prove by induction on $n$. When $n = 1$, if $C_1$ is of the form $A \leftarrow$, Step 3 of IncrOpt adds $C_1$ to $P_1$. Then it is obvious that the least model of $C_1$ is the set $\{A\}$. On the other hand, if $C_1$ is of the form $A \leftarrow B_1 \wedge \cdots \wedge B_m$, Step 2 of IncrOpt adds $C_1$ to $P_{1,d}$ and $P_1$ becomes empty. Then it is easy to see that the least model of $C_1$ is the empty set. Now assume that the lemma is true for $n = k - 1$. There are two cases.

**Case 1.** $C_k$ is added to $P_{k,d}$. This must occur in Step 2 of IncrOpt, and $C_k$ is of the form $A \leftarrow B_1 \wedge \cdots \wedge B_m$ such that there exists a $B_j$ for $1 \leq j \leq m$ that appears as a node in the DC-graph $G_k$. There are two subcases. First, $B_j$ may be added as a node in Step 1 of IncrOpt, in which case $B_j$ appears for the first time and must not be in the least model of $C_1, \ldots, C_k$. Alternatively, $B_j$ may be a node in DC-graph $G_{k-1}$. Then according to Lemma 3.2, $B_j$ cannot be the head of a clause in $P_k$. By the induction assumption, $B_j$ is not in the least model of $C_1, \ldots, C_{k-1}$, and hence not in the least model of $C_1, \ldots, C_k$. By combining the two subcases, it is necessary that the least model of $C_1, \ldots, C_k$ is the same as the least model of $C_1, \ldots, C_{k-1}$. By the induction assumption, the latter is the set $\{A | A$ is the head of a clause in $P_{k-1}\}$, but since $C_k$ is added to $P_{k,d}$, it is necessary that $P_k = P_{k-1}$.

**Case 2.** $C_k$ is added to $P_k$. Let $C_k$ be of the form $A \leftarrow B_1 \wedge \cdots \wedge B_m$. There are again two subcases depending on whether Subroutine Remove is invoked. First, consider the subcase when Remove is not called. Then $P_k = P_{k-1} \cup C_k$ and thus
\{B \mid B \text{ is the head of a clause in } P_k\} \text{ is equal to } \{A\} \cup \{B \mid B \text{ is the head of a clause in } P_{k-1}\}. \text{ Moreover, } C_{l_1} \text{ is added to } P_k \text{ in Step 3 of IncrOpt. This is possible only if all } B_j \text{ do not occur as nodes in } G_{k-1}. \text{ Then according to Lemma 3.2, all } B_j \text{ occur as heads of clauses in } P_{k-1}. \text{ By the induction assumption, all } B_j \text{ are in the least model of } C_{l_1}, \ldots, C_{l_{k-1}}\}. \text{ Thus, } A \text{ is in the least model of } C_{l_1}, \ldots, C_{l_k}.

Now consider the subcase when Subroutine Remove is called. A clause Cl may be added to } P_k \text{ in Step 2b or 3 of Remove. If } Cl \text{ is added in Step 2b, } Cl \text{ is of the form } B \leftarrow A \land B_1 \land \cdots \land B_m, \text{ where } A \text{ occurs as the head of a clause in } P_k, \text{ and thus is in the least model based on the analysis for the first subcase. Moreover, due to the condition of Step 2b, } B_1, \ldots, B_m \text{ must all be in the least model as well. Thus, } B \text{ has to be in the least model. Alternatively, if } Cl \text{ is added in Step 3 of Remove, this is possible only if all atoms in the body of } Cl \text{ are not in the DC-graph and are in the least model. Hence, the head of } Cl \text{ must also be in the least model. } \square

The lemma above shows that when applying Algorithm IncrOpt to a definite program, once IncrOpt completes its execution, no further processing is needed to compute the least model. This is not the case for Algorithm Incr and Algorithm SizeOpt, as shown in the following example.

**Example 4.1.** Consider the definite program \{A \leftarrow B, B \leftarrow A, C \leftarrow, D \leftarrow C\}. All four clauses remain if either Algorithm Incr or Algorithm SizeOpt is applied. The application of a least-model solver is then needed to compute the least model \{C, D\}. However, if Algorithm IncrOpt is used instead, only the clauses } C \leftarrow \text{ and } D \leftarrow C \text{ remain, whose heads directly give the least model.

One may wonder whether the above lemma can be generalized to disjunctive programs in the following sense. If } P \text{ is a disjunctive program consisting of clauses } C_{l_1}, \ldots, C_{l_n} \text{ and } \text{incoopt}(\cdots \text{incoopt}(\langle \emptyset, \emptyset, \emptyset \rangle, C_{l_1}), \ldots, C_{l_n}) = (P_n, P_{n.d}, G_n), \text{ then is it true that for all atoms } A \text{ that appears in the head of a clause in } P_n, A \text{ occurs in some minimal model of } P? \text{ The answer is no. Consider } P = (A \lor B \leftarrow, A \leftarrow, C \leftarrow B). \text{ Applying IncrOpt does not cause any change. Thus, the set of atoms appearing in the heads is } \{A, B, C\}. \text{ However, } B \text{ and } C \text{ are not contained in the (unique) minimal model of } P.

According to Corollary 3.1 and Lemma 4.1, when using Algorithm IncrOpt, different orders of inserting the same collection of clauses do not affect the final DC-graph, and the final sets of retained and deleted clauses. However, different orders may require different execution times—depending largely upon how many times Subroutine Remove is invoked. If Remove is not called at all when inserting a clause } A_1 \lor \cdots \lor A_m \leftarrow B_1 \land \cdots \land B_l, \text{ the complexity of Algorithm IncrOpt is } O(ml). \text{ Otherwise, if } a \text{ is the number of nodes (atoms) in the current graph, then the worst case complexity of recursively calling Remove is } O(alN), \text{ and that of IncrOpt is } O(ml + alN). \text{ It is then tempting to conclude that the complexity of IncrOpt for inserting } n \text{ clauses is } O(n(ml + alN)). \text{ However, this is incorrect.}

\footnote{Recall from the discussion in Section 2.2 that if there are } n \text{ clauses in the original nonground program } P, \text{ there are exactly the same number of clauses to be dealt with by IncOpt. This is because IncOpt does not involve "grounding out" the program, which may have the effect of exploding } n \text{ to a very large value of the form } nx^n, \text{ where } y \text{ depends on the arities of the predicates and } x \text{ depends on the size of the Herbrand base of the program.}
because during the process of inserting the $n$ clauses, Remove($A$) for all atoms $A$ can only occur at most once. Thus, for inserting $n$ clauses, the complexity of IncrOpt should be $O(nml + al(N + n))$.

On the other hand, if Algorithm SizeOpt is used directly, then there are $(N + n)$ clauses. The worst case complexity of Algorithm SizeOpt for $(N + n)$ clauses is $O(ml(N + n)^2)$. Thus, comparing the complexity figures of Algorithm SizeOpt and IncrOpt does not provide any clear conclusion, as the comparison depends on the magnitude of $a$, the number of atoms in a DC-graph, relative to the magnitudes of $N$, $n$, $l$, and $m$. In Section 5, we will present experimental results evaluating the effectiveness of Algorithm IncrOpt.

### 4.2. Heuristics: Ordering Clauses to Be Inserted

The above coarse-grained complexity analysis of Algorithm IncrOpt reveals that given $n$ clauses to be inserted, the most efficient order is the one that minimizes the number of times Subroutine Remove needs to be called. In the following, we discuss three possible ways to insert $n$ clauses. The most obvious way is to use IncrOpt to insert the clauses in an arbitrary order (e.g., textual order). For lack of a better name, we will refer to this strategy as IncrOptArb. To the other extreme, another way to insert $n$ clauses is to really try to minimize the number of times Subroutine Remove will be called. The following algorithm uses a heuristic order that attempts to do that.

**Algorithm IncrOptOrder.** Let $C_1, \ldots, C_n$ be the clauses to be inserted.

1. Initialize $R$ to all the facts among $C_1, \ldots, C_n$ and initialize $S$ to $\emptyset$.
2. For each clause $C_l \in R$:
   (a) Call Algorithm IncrOpt with $C_l$.
   (b) If $C_l$ is not added to the DC-graph, then for each atom $A$ in the head of $C_l$, add all the clauses not considered so far with $A$ in the body to $S$.
3. If $S$ is not empty, set $R$ to $S$ and $S$ to $\emptyset$. Go to Step 2.
4. Apply IncrOpt on each of the clauses not considered so far in an arbitrary order.

**Example 4.2.** Suppose the six clauses of $P$ and $P'$ in Examples 2.1 and 2.2 are to be inserted. Clause 5 is the first one considered. Since IncrOpt does not add Clause 5 to the DC-graph, clauses 1 and 6 are added to the set $S$ and inserted in the next iteration of IncrOptOrder. While clause 1 is added to the DC-graph, clause 6 is not, which causes 2 and 3 to be considered in the third iteration. This time both clauses are added to the DC-graph. Then Step 4 of IncrOptOrder applies IncrOpt to clause 4, the only clause remaining.

Notice that if clause 5 is inserted after clause 1, then node $C$ created during the insertion of clause 1 will need to be removed. Similarly, if clause 6 is inserted after

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4 Based on Figure 2, the analysis here assumes that $P$ consists of $N$ clauses and $P_0'$ consists of $n$ clauses.
clause 2, then node E will need to be removed. To prevent all these unnecessary insertions/removals from happening, IncrOptOrder inserts facts first and follows Step 2b.

One possible weakness of Algorithm IncrOptOrder is that there may be too much overhead involved in implementing Step 2. The following algorithm represents a compromise. It inserts the facts among the n clauses first, but leaves the remaining clauses to be inserted in whatever order.

**Algorithm IncrOptFact.** Let Cl₁, ..., Clₙ be the clauses to be inserted. Apply Algorithm IncrOpt first to all the facts among the clauses. Then apply Algorithm IncrOpt to the remaining clauses in an arbitrary order.

In Section 5, we will present experimental results evaluating the effectiveness of these three algorithms.

### 4.3. Avoiding Redundant Node Expansion

As described in Section 2.1, for each conflict-set unifier θ of a node in a partial instantiation tree, there is a child node processing P ∪ θ. The lemma below attempts to reduce the time taken to expand a partial instantiation tree by not expanding those nodes that can be predicted to be identical to nodes that have already been generated. It gives three sufficient conditions which are very easy to implement. Without loss of generality, it assumes that substitutions in conflict-set unifiers are represented in solved form [19]. That is, for a set of (substitution) equations, the equations are of the form Xᵢ = tᵢ and all variables appearing in the left-hand side of the equations cannot appear in the right-hand side of any equation. For the following lemma, we use the notation L(θ) and R(θ) to denote the set of all variables appearing in the left- and right-hand-side of θ, respectively. We also use the notation P =ₜ P₁ to denote the fact that the node for program P is the parent of the node for P₁, and θ is the conflict-set unifier, i.e., P₁ = P ∪ θ.₀

**Lemma 4.3.** 1. Given P₁ =ₜ P₂ and P₁ =ₜ P₃, it is necessary that P₂ = P₃.

2. Given P₁ =ₜ P₂ =ₜ P₃ =ₜ P₄, and P =ₜ P₁ =ₜ P₄, P₂ = P₄ if L(θ₁) ∩ L(θ₂) = ∅, L(θ₃) ∩ R(θ₃) = ∅, and R(θ₃) ∩ L(θ₄) = ∅.

3. Given P₁ =ₜ P₂ =ₜ P₃ =ₜ P₄ if L(θ₃) ∩ R(θ₃) = ∅.

**Proof Outline.** For space considerations, we only show a proof outline for part 3. By definition, P₃ = P₂ ∪ P₁.θ₁. Substituting P₂ = P₁ ∪ P₁.θ₁ into (P₂ ∪ P₁.θ₁), we get P₃ = P₁ ∪ P₁.θ₂ ∪ P₁.θ₁ ∪ P₁.θ₁.θ₁. Since L(θ₁) ∩ R(θ₂) = ∅, P₁.θ₁.θ₁ = P₁.θ₂. Then it is straightforward to verify that by substituting P₂ = P₁ ∪ P₁.θ₁, P₃ = P₂. 

As an example consider again the program P discussed in Section 2.1. As shown in Figure 1, P₂, which is defined by P = P ∪ P₂, has two child nodes corresponding to the conflict-set unifiers θ₁ and θ₂. Then according to the first part of the above lemma, there is no need to expand the node P₃ = P₂ ∪ P₁.θ₁, because P₃ is identical to P₂ by the second part of the lemma, there is no need to expand the node P₆. In the next section, we will present experimental results showing the effectiveness of the optimizations described by the lemma.
5. IMPLEMENTATION OVERVIEW AND EXPERIMENTAL EVALUATION

In this section, we will present experimental results evaluating the effectiveness of the proposed algorithms and optimizations. Before we do this, we will first give an overview of the implementation of these algorithms and optimizations, as well as the implementation of the entire framework that includes both the evaluation and partial instantiation phases.

5.1. Implementation Overview of the Proposed Algorithms and Optimizations

For our experimentation, we implemented Algorithms IncrOpt (and thus trivially IncrOptArb), IncrOptOrder, and IncrOptFact in C. We also implemented two versions of Algorithm SizeOpt. One is a straightforward encoding of the algorithm presented in Section 2.2 in C. The other one tries to minimize searching by extensive indexing. Unfortunately, in all the experiments we have carried out so far, the version with extensive indexing requires so much overhead to set up the indices that the straightforward version takes much less time. Thus, for all the experimental results reported later for Algorithm SizeOpt, the straightforward version was used.

Recall that in our incremental algorithms, a DC-graph is used to organize the deleted clauses. Each arc in the graph represents a deleted clause. However, not every deleted clause has a corresponding arc in the graph. Given a deleted clause $C_l = A_1 \lor \ldots \lor A_m \leftarrow B_1 \land \ldots \land B_n$, if all of $A_1, \ldots, A_m$ do not appear in the graph, then this clause would not appear as a label of an arc. In our implementation of the incremental algorithms, we set up a virtual node so that there is an arc from the appropriate node of an atom appearing in the body to the virtual node. More precisely, a virtual node is an atom that appears both in the heads of some clauses in $Q$ and in the heads of some clauses in $Q_d$. In this way, each deleted clause has a corresponding arc in the DC-graph. This simplifies the construction and maintenance of DC-graph, and makes the implementation more efficient. This is because with the use of virtual nodes, Step 3 of Subroutine Remove can be skipped. Finally, to further speed up the maintenance of DC-graphs, a counter is kept for each clause which records the number of times the clause appears as an arc in the graph. If this counter decreases to zero, the clause is removed from $Q_d$ and put back to $Q$.

5.2. Implementation Overview of the Entire Framework

Apart from the proposed algorithms and optimizations, we also implemented the entire partial instantiation framework that given an input logic program, computes the entire partial instantiation tree. The entire system was written in C running under the UNIX environment, and has roughly 3000 lines of code. In the following, we summarize the main aspects of the implementation and highlight how we tried to make the implementation as space and run-time efficient as possible.

There are four major data structures used in the system: a term table, an atom table, a clause table, and a partial instantiation tree structure. First, all the terms are organized in a global term table, in which each term is identified by an index.
Associated with each term are such pieces of information as the type (i.e., constant, variable, or function), arity, name, and pointers to the parameters of the term. At the root node of the partial instantiation tree, the term table only consists of those terms that are in the original program. When a child node is created, new terms generated via unification are added to the end of the term table. Note that when a child node and its subtree have been fully expanded, the part of the term table corresponding to the entire subtree can be thrown away. This leads to two implementation decisions. First, the expansion of a partial instantiation tree is conducted in a depth-first manner. Second, the term table is implemented as a stack. These decisions help to minimize the run-time space requirement of our system.

Every atom is stored in a global atom table which keeps track of such information as the name, arity, and the terms (represented by their indices to the term table) that appear in the atom. Like the term table, the atom table is organized as a stack. Similarly, there is a global clause table/stack which records for each clause the atoms appearing in the clause, in the form of indices to the atom table. Recall that when a child node is to be created, the program \( P \) at the parent node will be instantiated to \( P \cup P\theta \). To facilitate the comparisons of the clauses in \( P\theta \) with the existing clauses in \( P \), atom indices in the clause table are kept in ascending order.

Furthermore, there is a partial instantiation tree structure. Apart from the usual parent and children pointers, each node has pointers to the set of unifiers, the true and false sets, and the appropriate DC-graphs. It also contains indices to the clause, atom and term tables. Again once a subtree has been fully expanded, as much space previously occupied by its nodes as possible is freed for future reuse.

Given a program \( P \) in a parent node and a conflict-set unifier \( \theta \), the program in the child node \( P \cup P\theta \) is obtained by first getting all the appropriate unified terms \( T\theta \). There are three possibilities for \( T\theta \). It may be \( T \) itself, the same as some existing term in the term table, or an entirely new term. In the latest case, the new term is added to the term table, and a pointer from \( T \) to \( T\theta \) is created. This kind of pointer will assist in the (possible) insertion of a new, unified atom \( A\theta \) into the atom table. This insertion in turn creates a pointer from atom \( A \) to \( A\theta \). Again this kind of pointer facilitates the insertion of unified clauses to the clause table.

It is obvious that in generating a child node, a lot of comparisons for terms, atoms, and clauses need to be made. In particular, to check whether a term/atom/clause is new or not, it is compared with every term/atom/clause in the appropriate tables. Thus, our implementation of the tables as stacks not only reduces run-time memory space requirement, but also minimizes the time taken for comparisons. Furthermore, as discussed above, comparisons are facilitated by keeping atom indices in ascending order in the clause table.

In partial instantiation, generating the conflict-set unifiers is a key step at each node. Thus, the efficiency of the unification algorithm is one of the key factors determining the overall performance of the system. Among the unification algorithms that have been proposed so far (e.g., [7, 19]), we chose to implement the version developed by Martelli and Montanari [19], with a few optimizations. For instance, a key optimization is to keep all the variables appearing in the left-hand sides of substitution equations in sorted order. Thus, unifiers can be compared more efficiently.

In the remainder of this section, we will report experimental results evaluating the effectiveness of our proposed algorithms and optimizations. All run-times are
in milliseconds and were obtained by running the experiments in a SPARC-LX Unix time-sharing environment.

5.3. **IncrOptFact vs IncrOptOrder vs IncrOptArb**

In this series of experiments, we compared the effectiveness of the heuristics described in Section 4.2. The following tabular results are very representative of all the experiments we conducted. The times below count the time taken for each algorithm to process 20 clauses. At most 5 atoms appear in the head of each clause and at most 10 appear in the body. All atoms in the heads and bodies, as well as their numbers, are randomly generated.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Processing time for 20 clauses (ms)</th>
<th>Rules deleted</th>
<th>Time to find minimal models (ms)</th>
<th>Total time taken (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IncrOptFact</td>
<td>3.5</td>
<td>19.0</td>
<td>49.17</td>
<td>52.71</td>
</tr>
<tr>
<td>IncrOptArb</td>
<td>3.6</td>
<td>0.0</td>
<td>83.61</td>
<td>83.94</td>
</tr>
<tr>
<td>IncrOptOrder</td>
<td>150.6</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Recall that IncrOptOrder tries to minimize the number of times Subroutine Remove needs to be called by first inserting the facts and then partially ordering the insertion of the remaining clauses. Clearly shown above, the strategy backfires as it requires too much overhead. Inserting a set of clauses in arbitrary order, as shown in the third column of the above table, performs surprisingly well. However IncrOptFact is considered to be the best, not so much because it outperforms IncrOptArb by a wide margin, but rather because it is very simple to implement and almost always performs better than IncrOptArb. In the remainder of this section, we will only report the results of IncrOptFact.

5.4. **Same Number of Disjunctive Clauses: IncrOptFact versus SizeOpt**

In this series of experiments, we compared the effectiveness of our incremental algorithm IncrOptFact with the original algorithm SizeOpt (see Table 1). For each algorithm, we report (i) the total time taken to process the 20 clauses used in Section 5.3, (ii) the number of clauses deleted and (iii) the time taken to find the minimal models. For just the time taken to process the 20 clauses, our incremental algorithm IncrOptFact takes more time than SizeOpt, primarily for maintaining DC-graphs. However, as shown in the table, the extra time is worth spending because IncrOptFact manages to delete 19 more clauses than SizeOpt. This is all due to the fact that, as described in Section 4.1, IncrOptFact deletes all the clauses in self-sustaining cycles. Consequently, the times taken for the two algorithms to find the (same collection of) minimal models differs by a wide margin. This clearly demonstrates the importance of deleting more rules, whose impact is multiplied in model computations. At the end, the total time taken by IncrOptFact is only about 60% of the time taken by SizeOpt.

**TABLE 1**

<table>
<thead>
<tr>
<th></th>
<th>IncrOptFact</th>
<th>SizeOpt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing time for 20 clauses (ms)</td>
<td>3.54</td>
<td>0.33</td>
</tr>
<tr>
<td>Rules deleted</td>
<td>19.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Time to find minimal models (ms)</td>
<td>49.17</td>
<td>83.61</td>
</tr>
<tr>
<td>Total time taken (ms)</td>
<td>52.71</td>
<td>83.94</td>
</tr>
</tbody>
</table>
TABLE 2

<table>
<thead>
<tr>
<th></th>
<th>IncrOptFact</th>
<th>SizeOpt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing time for 100 clauses (ms)</td>
<td>9.22</td>
<td>0.73</td>
</tr>
<tr>
<td>Rules deleted</td>
<td>89.0</td>
<td>17.0</td>
</tr>
<tr>
<td>Time to find least model (ms)</td>
<td>5.76</td>
<td>580.06</td>
</tr>
<tr>
<td>Total time taken (ms)</td>
<td>14.98</td>
<td>580.79</td>
</tr>
</tbody>
</table>

5.5. Same Number of Definite Clauses: IncrOptFact versus SizeOpt

Based on the results of the previous set of experiments for disjunctive clauses, we surely can predict that for definite clauses, IncrOptFact again outperforms SizeOpt. Moreover, Lemma 4.2 presents a stronger reason for us to believe that IncrOptFact will perform even better. The lemma shows that for definite clauses, our incremental algorithms can obtain the least model by simply obtaining the heads of all the clauses not deleted. Indeed, our belief is confirmed by this series of experiments, in which each test program contains 100 randomly generated definite clauses. Table 2 reports the run-times for a typical program. The processing time taken by IncrOptFact is longer than that by SizeOpt, but again IncrOptFact deletes many more clauses and requires a minimal amount of time to obtain the least model. In contrast, SizeOpt is much less effective in deleting clauses and requires the invocation of the least model solver whose run-time dominates the entire process.

5.6. Partial Instantiation Trees: IncrOptFact vs SizeOpt

Thus far, we have only compared IncrOptFact with SizeOpt in those situations where both algorithms are required to process the same number of clauses. However, recall that our incremental algorithms are designed for a slightly different purpose: to expand partial instantiation trees efficiently. As described in Section 2.1, if program $P$ in a node $N$ gives rise to conflict-set unifiers $\theta_1, \ldots, \theta_m$, then $N$ has $m$ child nodes each corresponding to $P \cup \theta_j$. Thus, as shown in Figure 2, the acid test of the effectiveness of our incremental algorithms is between the time taken for our incremental algorithms to process the clauses in $P\theta_j$ and the time taken for SizeOpt to process all the clauses in $P \cup P\theta_j$. Given the results of the previous series of experiments, we expect IncrOptFact to outperform SizeOpt even more in the expansion of partial instantiation trees. This conjecture is confirmed by the following experiment that fully expands the instantiation tree of the program discussed in Section 2.1.

By applying the heuristics of avoiding redundant node expansion discussed in Section 4.3, our algorithm only needs to process 5 nodes (i.e., the root node and nodes 1, 2, 4, and 5), as compared with 11 that would be needed otherwise (cf. Figure 1). This demonstrates the usefulness of the heuristics. Table 3 compares IncrOptFact with SizeOpt for the expansion of five nodes only. In other words, the total run-time taken by SizeOpt to expand 11 nodes would be even higher than the time recorded in the table. Each entry in Table 3 gives two run-times: (i) the time taken to process the clauses in $P\theta_j$ by IncrOptFact or in $P \cup P\theta_j$ by SizeOpt and (ii) the time take to find the least model.
### TABLE 3

<table>
<thead>
<tr>
<th></th>
<th>IncrOptFact</th>
<th>SizeOpt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node 1 (ms)</td>
<td>0.67/5.47</td>
<td>0.33/45.88</td>
</tr>
<tr>
<td>Node 2 (ms)</td>
<td>0.02/5.57</td>
<td>0.34/45.86</td>
</tr>
<tr>
<td>Node 3 (ms)</td>
<td>0.02/5.57</td>
<td>0.34/53.95</td>
</tr>
<tr>
<td>Node 4 (ms)</td>
<td>0.02/5.49</td>
<td>0.34/49.19</td>
</tr>
<tr>
<td>Node 5 (ms)</td>
<td>0.02/5.57</td>
<td>0.34/52.88</td>
</tr>
<tr>
<td>Total (time)</td>
<td>0.75/27.67</td>
<td>1.69/247.76</td>
</tr>
<tr>
<td>Total (time +</td>
<td>28.42</td>
<td>249.45</td>
</tr>
</tbody>
</table>

As expected, the processing time of IncrOptFact for the first node is relatively long (i.e., 0.67 ms), whereas the processing times for subsequent nodes are much shorter (i.e., 0.02 ms). This reflects the benefit of being incremental. At the end, the total processing time of IncrOptFact is 0.75 ms, less than 50% of that of SizeOpt. Furthermore, as shown in previous experiments, IncrOptFact requires much less time in finding least models. Thus, the conclusion is very obvious and convincing: the time taken to expand the five nodes by using IncrOptFact is merely over 10% of the time taken by using SizeOpt.

### 6. CONCLUSIONS

The objective of this paper was to study how to optimize the expansion of partial instantiation trees for computing minimal and least models. Toward this goal, we have developed Algorithm Incr, which is formally proved to be incremental. We have further optimized Incr to delete clauses in self-sustaining cycles, to partially order clauses to be inserted, and to avoid expanding redundant nodes. These optimizations lead to several algorithms, among which experimental results indicate that IncrOptFact gives the best performance. More importantly, when compared with the original algorithm SizeOpt, IncrOptFact can give very significant improvement in run-time efficiency. Last but not least, it should be kept in mind that even though our algorithms appear to be purely propositional, they are, in conjunction with partial instantiation, immediately applicable to programs that may contain variables and function symbols. Furthermore, they are not restricted to model solving techniques that are based on mixed integer programming, but are generally applicable to any model solving algorithms.

In ongoing work, we investigate the optimal order to expand nodes in partial instantiation trees, in terms of both space and time efficiency. In situations where it is not desirable or too costly to generate an entire partial instantiation tree, we will study how to generate portions of the tree selectively.

### REFERENCES